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Abstract: An uncalibrated distributed multiphysics snow model driven by downscaled weather forecasts (30-m, 15-min) was implemented as a Radar Observing System Simulator (ROSS) in Senator Beck Basin (SBB), Colorado to elucidate topographic controls on C-, X- and Ku-bands active microwave sensing of mountain snowpacks. Phase-space maps of time-evolving grid-scale ROSS volume backscatter show the accumulation branch of the backscatter-snow water equivalent (-SWE) hysteresis seasonal loop that is the physical basis for radar retrieval (direct inference) of SWE and snowpack physical properties. ROSS results with snow-ground scattering correction inferred from snow-free conditions capture well the seasonal march of Sentinel-1 C-band backscatter, including spatial patterns tied to elevation, slope, and aspect. Root Mean Square Deviations (RMSDs) do not exceed ± 3.2 dB for ripening snowpacks in early spring and ± 2.4 dB for dry snowpacks in the accumulation season when the mean absolute bias is < 1 dB for all land-cover types with topographic slopes 30°. Grid-point RMSDs are attributed to the underestimation of snowfall on upwind slopes compounded with forecast errors for the weather near the ground. Like Sentinel-1, ROSS backscatter fields exhibit frequency-independent single-scaling behavior within the 60-150 m scale range for dry snowpacks in the accumulation season, while frequency-dependent scaling behavior emerges in the ablation season. This study demonstrates skillful physical modeling capabilities to emulate Sentinel-1 observations in complex terrain. Conversely, it suggests high readiness to retrieve snow mass and snowpack properties in mountainous regions from radar measurements at high-spatial resolutions enabled by SAR technology.

Keywords: topographic controls; microwave behavior; seasonal snow; modeling framework; scaling analysis

. Introduction

Snowfall deposition and accumulation in mountainous watersheds characterized by complex topography and marked altitudinal gradients are highly heterogeneous and closely tied to elevation and aspect (Essery and Pomeroy, 2004; Lopez-Moreno and Stahli, 2008). The spatial heterogeneity of the snowpack, in turn, impacts hydrological processes such as melt and runoff (Anderton et al., 2002; Colbeck, 1979; DeBeer and Pomeroy, 2017; Marsh and Woo, 1985). Therefore, capturing the spatial variability of snowfall deposition and accumulation is essential to model alpine hydrology and snow water resources in mountainous areas (Erickson et al., 2005; Jost et al., 2007). Due to the large errors in snowfall deposition forecasts and the challenges and high costs of ground observations in remote high elevation watersheds, satellite-based remote sensing monitoring of snow water equivalent (SWE) is necessary. However, the spatial arrangement of topography within microwave footprints has a significant non-linear influence on snowpack radiative signals. For example, topographic reliefs with hillslopes cast shadows and alter relative viewing angles at different locations within the same view field (Dong et al., 2005; Smith and Bookhagen, 2016), which can modify the relative strengths of horizontally and vertically polarized brightness temperature (Dozier and Warren, 1982), and thus introduce ambiguity in the estimation (retrieval) of geophysical states at the microwave measurement scale.

In the last decade, significant advances in deploying Synthetic Aperture Radar (SAR) technology have enabled global remote sensing measurements at high-spatial resolution. Using Sentinel 1 C-band data, Manickam and Barros (2020) demonstrated that SAR measurements of seasonal snow exhibit distinctive spatial characteristics uniquely tied to snowpack stratigraphy, landform, and land-cover resulting in remarkable single-scaling behavior of backscatter imagery at sub-kilometer scales for dry snow conditions. They also found area-variance scaling relationships that reach minima at scales in the 100-250 m range over complex terrain in the backscatter fields consistent with topographic controls on snow deposition and snowpack stratigraphy in the absence of trees. Multi-scaling emerges due to the characteristic length-scale of forest patchiness in the landscape. One important implication of these findings is that Sentinel-1 measurements upscaled to 100-250 m capture optimally physics-driven snowpack heterogeneity.

Systematic characterization of the active microwave behavior of seasonal snowpacks under realistic natural conditions is necessary to establish the physical basis for interpreting SAR measurements and retrieval algorithms. For this purpose, the Multilayer Snow Hydrology Model (MSHM, Cao and Barros, 2020) coupled to the Microwave Emission Model of Layered Snowpacks (MEMLS, Proksch et al., 2015) was introduced into the framework of the spatially distributed Duke Coupled Hydrology model (DCHM, Tao and Barros, 2018, 2019), hereafter referred to as the Distributed Snow Multiphysics Model (DSMM). DSMM was implemented at high spatial resolution (30-m) in High-Mountain Colorado as a Radar Observing System Simulator (ROSS) of the seasonal snowpack in the Senator Beck Basin (SBB) to examine how topographic controls on snow hydrologic processes are manifest in multi-frequency radar backscatter (C-, X- and Ku-bands). Further, distributed synthetic radar measurements predicted by ROSS driven by weather forecasts were evaluated extensively against Sentinel-1 C-band SAR daytime orbit data. This manuscript is organized as follows: Section 2 describes the study area and available datasets. Methods are detailed in Section 3, and the results and data analysis are presented in Section 4. Section 5 is the conclusions.

2. Study Area and Datasets

2.1 Senator Beck Basin

The 2.91 km^2 Senator Beck Basin area (37.85°N ~ 37.94°N, 107.75°W ~ 107.67°W) is nestled in the western San Juan Mountains of southwestern Colorado (**Fig. 1**). SBB is a typical Hight Mountain headwaters catchment with elevations ranging from 3362 m (basin outlet) to 4118 m (basin summit). SBB landcover is principally cold grassland with the alpine forest at low elevations (Landry et al., 2014).

2.2 Atmospheric Forcing and Ancillary Data

The High-Resolution Rapid Refresh (HRRR) weather prediction model produces hourly forecasts at 3 km resolution across the continental United States with up to 18 h lead time (Benjamin et al., 2016). The first HRRR hour (+01 hr) forecasts of near-surface air temperature, snowfall and rainfall rate, air pressure, incoming shortwave and longwave radiation, wind speed, and specific humidity were meteorological forcings in this study. The HRRR data were downloaded from the Center for High-Performance Computing at the University of Utah (Blaylock et al., 2017) for nine grid points encompassing SBB (**Fig. 1**). The native (3km, hourly) data were bi-linearly interpolated into 3030 m^2 grid cells, and then linearly interpolated in time to 15-min intervals from September 1st, 2016 to July 28th, 2017. Air temperature at 2-m above ground and incoming shortwave radiation were topographically corrected as per Tao and Barros (2018). Spatially distributed gap-filled shortwave broadband albedo data were derived directly from MODIS products (**Table 1**, Section 3.2 for methodology) following Tao and Barros (2019).

2.3 Sentinel-1 SAR Measurements

The C-band (5.405 GHz) Sentinel-1 Level-1 single-look complex data in the Interferometric Wide swath mode processed to 1515 m^2 were fractally upscaled to 3030 m^2 following Bindlish and Barros (1996). The geometric distortions in Sentinel images were identified and screened out via the Sentinel Application Platform modules. Data consisting of co-pol (VV) and cross-pol (VH) backscattering intensity in descending path were explored in this study.

2.4 Ground Observations

The Center for Snow and Avalanche Studies (CSAS) has operated two field sites (SBSP and SASP in **Fig. 1**) including instrumented meteorological towers and a broad-crested notched weir (SBSG in **Fig. 1**) in the SBB since 2003. Data collected at the sites contain hourly measurements of meteorological variables (precipitation, temperature, humidity, wind, radiation fluxes, and atmospheric pressure), snow depth, as well as streamflow starting in the water year 2005

(Landry et al., 2014). Time series of snow profiles are manually collected at SBSP and SASP throughout the winter season. The archived data (Center for Snow and Avalanche Studies, 2013) can be obtained from https://snowstudies.org/archived-data/.

In the present study, observations of SWE, snow depth, and streamflow between September 1$^{\mathrm{st}}$, 2016 and July 28$^{\mathrm{th}}$, 2017 were selected to evaluate the downscaled HRRR weather forecasts and assess the DSMM seasonal snow hydrology regime in the SBB (Section 4.3.1).

3. Methods

3.1 Air Temperature Correction

To bridge the large spatial gap between the raw HRRR forecasts resolution (3 km) and the DSMM high-spatial one (30-m) needed to capture complex topography, simple interpolation of air temperature with altitude is not adequate, and a geopotential correction is necessary (Hamill, 2020; Hamill and Scheuerer, 2020; Tao and Barros, 2018). Consequently, the dynamic lapse rate (in K/m) was estimated from the HRRR temperature profile at two isobaric levels (700 and 500 hPa) above the local elevation for each 30-m pixel at each time step (15-min), and the corrected HRRR air temperature T_{cor} (K) at 2-m height is as follows:

$$T_{\mathrm{cor}} = T_{\mathrm{HRRR}} + \Gamma \times \ z = T_{\mathrm{HRRR}} + \frac{T_{700}-T_{500}}{H_{700}-H_{500}} \times \ z\#(1)$$

where z is the elevation difference between the HRRR terrain elevation and the 30-m SRTM DEM (Shuttle Radar Topography Mission Digital Elevation Model) elevation; T_{700} and T_{500} are the HRRR temperature data at 700 hPa and 500 hPa, respectively; and H_{700} and H_{500} are HRRR geopotential heights at the corresponding pressure levels.

3.2 Surface Shortwave Broadband Albedo

The sequential workflow to produce 30-m, 15-min land surface albedo from MODIS and HRRR products adapted from Tao and Barros (2019) is laid out in **Fig. 2**. The raw MODIS and HRRR data over the SBB were spatially, bilinearly interpolated to the 3030 m^2, then temporally, linearly interpolated to 15-min steps. Quality control includes filtering to eliminate cloud artifacts and data gap-filling to replace missing data.

Before calculating blue sky (actual) albedo, HRRR surface pressure, 30-m SRTM DEM, and MODIS MOD11B1 & MYD11B1 land surface temperature data were fed into the Solar Position Algorithm from the National Renewable Energy Laboratory (Reda and Andreas, 2004) to compute the hourly solar zenith angle (SZA) for each grid point. Since the multi-angle implementation of atmospheric correction (MAIAC) aerosol optical depth data that contain multiple orbit overpasses from both Terra and Aqua satellites did not produce reliable Atmospheric Optical Depth (AOD) over snow (Lyapustin and Wang, 2018), we employed HRRR cloudiness and snow cover information to extract AOD values on "clean air" days (snow cover and total cloud cover were both less or equal to 30%). After that, the AOD for cloudy pixels was corrected by the value on the nearest "clean air" day, and the mean AOD from all "clean air" days was computed for snow-covered pixels.

Due to the lack of finer resolution albedo data accounting for local illumination geometry and instantaneous SZA, we restored to the MCD43A3 product that has been evaluated globally over representative locations and periods (Jin et al., 2003; Liang et al., 2002; Schaaf et al., 2008; Wang et al., 2019b) to obtain the SZA-dependent black-sky albedo (BSA) α_{bs} and the white-sky albedo (WSA) α_{ws} in terms of the Ross-Thick/Li-Sparse BRDF model (Schaaf et al., 2002):

$$\alpha_{\text{bs}}(\theta,\lambda) = \begin{array}{c} f_{\text{iso}}(\lambda) \times \left(g_{0,iso} + g_{1,iso}\theta^2 + g_{2,iso}\theta^3\right) + \\ f_{\text{vol}}(\lambda) \times \left(g_{0,vol} + g_{1,vol}\theta^2 + g_{2,vol}\theta^3\right) + \\ f_{\text{geo}}(\lambda) \times \left(g_{0,geo} + g_{1,geo}\theta^2 + g_{2,geo}\theta^3\right) \end{array} \#(2)$$

$$\alpha_{\text{ws}}(\lambda) = f_{\text{iso}}(\lambda) + 0.189184 \times f_{\text{vol}}(\lambda) - 1.377622 \times f_{\text{geo}}(\lambda) \#(3)$$

of which θ is the SZA; λ indicates a MODIS spectral band (specifically 1-7 in this paper); $f_{\text{iso}}(\lambda)$, $f_{\text{vol}}(\lambda)$, and $f_{\text{geo}}(\lambda)$ are the kernel parameters marking the isotropic, volumetric, and geometric scattering, respectively; $g_{0,k}$, $g_{1,k}$, and $g_{2,k}$ ($k \in \{iso, vol, geo\}$) are constants.

To mitigate unreliable aerosol retrievals of the MCD43's upstream surface reflectance data (Lyapustin and Wang, 2018), albedo quality flags (MCD43A2) were utilized to isolate and retain the retrieved results with "best" and "good" quality. However, this quality filtering resulted in extensive missing data over the SBB. So the robust "smoothn" function combining bi-square weights with Studentized residuals (Garcia, 2010) was applied to fill in data gaps.

Finally, the narrow-band actual sky albedo α at seven MODIS bands were modeled from the corresponding α_{bs} and α_{ws} weighted by the fraction of diffuse skylight $S\left(\theta, \tau(\lambda)\right)$ which is a function of θ and band-dependent AOD $\tau(\lambda)$ (Schaaf et al., 2002):

$$\alpha(\theta,\lambda) = \left[1 - S\left(\theta, \tau(\lambda)\right)\right] \times \alpha_{\text{bs}}(\theta,\lambda) + S\left(\theta, \tau(\lambda)\right) \times \alpha_{\text{ws}}(\lambda) \#(4)$$

then the shortwave broadband albedo $A(\theta)$ is the weighted sum of α at bands 1-7:

$$A(\theta) = 0.0036 + \sum_{i=1}^{7} c_i \times \alpha(\theta,\lambda) \#(5)$$

in which c_i is the conversion weight corresponding to MODIS bands 1-7 listed in **Table S2** (Liang et al., 1999).

3.3 Shortwave Radiation Correction

Following the workflow (**Fig. 3**) adapted from Tao and Barros (2018), the topographic correction of the HRRR downward shortwave radiation flux mainly relies on three auxiliary parameters: the local illumination angle θ_i, the sky view factor V_f, and the terrain configuration factor C_f. Apart from the local terrain slope, the height and azimuth of the Sun influence the diurnal and seasonal variations of the local illumination angle. V_f measures the total fraction of unobstructed sky seen on a slope in all directions, with a value of one indicating that the sky is entirely unobstructed while zero indicates that the sky (and diffuse radiation) is completely blocked by the surrounding terrain (e.g., at the bottom of narrowed valleys). C_f is the percentage of the hemispheric view receiving reflected radiation from the surrounding terrain at a certain pixel position and varies from 0 (only sky visible) to 1 (only terrain visible). Generally, a larger sky view factor leads to a smaller terrain configuration factor ($C_f \approx 1 - V_f$). Parameters V_f and C_f were calculated by the Topographic Horizons Toolbox (Dozier, 2021).

The total incoming shortwave radiation $\mathrm{SW}_{\downarrow}^{\mathrm{tot}}$ is composed of three components: the diffuse radiation flux $F_{\downarrow}^{\mathrm{diff}}$, direct irradiance $F_{\downarrow}^{\mathrm{dirct}}$, and upwelling reflected radiation $F_{\uparrow}$ from surrounding topography.

$$\mathrm{SW}_{\downarrow}^{\mathrm{tot}} = F_{\downarrow}^{\mathrm{diff}} \times V_f + F_{\downarrow}^{\mathrm{dirct}} \times \cos\theta_i + F_{\uparrow} \times C_f \#(6)$$

$$F_{\uparrow} = A(\theta) \times \left[F_{\downarrow}^{\mathrm{diff}} \times \left(1 - V_f\right) + F_{\downarrow}^{\mathrm{dirct}} \times \cos\theta_i\right] \#(7)$$

3.4 Distributed Snow Multiphysics Model (DSMM)

Figure 4 presents a schematic depiction of DSMM integrating three sub-models: MSHM for snowpack processes, DCHM for distributed hydrology, and MEMSL for microwave emission and scattering. In the implementation, runoff from snow melting is routed as overland flow into the channel directly without accounting for refreezing and remelting during routing. Therefore, temporary ponding on ice layers is not represented, resulting in a more flashy streamflow response (Colbeck, 1979). Also, the scattering contribution from the vegetation canopy with and without intercepted snow is not explicitly represented. Detailed descriptions and evaluations of the multilayer snow hydrology and the microwave emission and scattering models can be found respectively in Kang and Barros (2012) and Cao and Barros (2020). The distributed hydrology modeling framework is described by Tao and Barros (2013) and Tao et al. (2016).

Since wet-bulb temperature T_w is a better indicator than air temperature T_a for snow-rain partitioning (Ding et al., 2014), especially in the higher and drier continental mountainous regions in the Western United States (Wang et al., 2019a), this study calculated T_w as a function of T_a and relative humidity RH via an empirical equation (Stull, 2011):

$$T_w = \begin{array}{c} T_a \times \tan^{-1}\left[0.151977 \times (RH + 8.313659)^{0.5}\right] + \\ \tan^{-1}(T_a + RH) - \tan^{-1}(RH - 1.676331) + \\ 0.00391838 \times \mathrm{RH}^{1.5} \times \tan^{-1}(0.023101 \times RH) - 4.686035 \end{array} \#(8)$$

where the temperature units are [°C] and RH is expressed in [%].

Elevation-corrected downscaled HRRR air temperature (T_a) time-series at the two grid points coinciding with the two ground-validation sites' locations capture well the variation throughout the hydrologic year within the realistic range defined by the observational maxima and minima at the two meteorological towers (**Fig. 5**). Note that the HRRR data are gridded areal estimates, whereas the tower observations are point measurements, and thus the amplitude of the observed diurnal range is expected to be more significant.

The observational albedo value A^{obs} can be derived from radiation observations at the two tower sites as follows:

$$A^{\mathrm{obs}} = \frac{R^{\mathrm{up}}}{R^{\mathrm{down}} + R^{\mathrm{diff}}} \#(9)$$

where R^{up}, R^{down}, and $R^{\mathrm{diff}}$are respectively pyranometer-measured upward, downward, and diffusive shortwave broadband radiation fluxes in [W/m^2]. Despite quality control, the raw radiation flux data exhibit unphysical behavior, which results in unrealistic variability in the derived albedo estimates at SASP and SBSP, and thus post-processing is required.

The gridded albedo data derived for this study differs from the local tower estimates in two ways: 1) higher values in the second half of the accumulation season (e.g., February and March), thus leading to colder snowpack surface temperatures and delaying the onset of melt, and 2) persistent higher values through the end of June corresponding to a nearly two-week delay snowpack retreat. The latter was corrected by interpolating linearly between June 1$^{\mathrm{st}}$ and the date when snow-free conditions are reached at SASP and SBSP (**Fig. 6**) and distributing the correction linearly with elevation. The spatial maps in **Fig. 7** illustrate the intra-seasonal variations of the shortwave broadband albedo linked to snow cover and intrinsic land surface properties indicated by Eqs. 2 and 3. Independent evaluation of this albedo product can be done indirectly by monitoring the temporal evolution of melt runoff against the streamflow observations at the SBB outlet.

3.5 Scaling Analysis

The spatial statistics of simulated snowpack backscattering behavior at C-, X-, and Ku-bands as a function of scale were examined by aggregating the backscattering from 900 m^2 to ~0.13 km^2 as listed in **Table 2** to isolate relatively homogenous square areas within the heterogeneous SBB. Specifically, as marked in **Fig. 8**, three 720720 m^2 (= 2424 pixels) subregions (A, B, and C) with different landcover types were carefully identified at different altitudinal bands for scaling analysis. The closeness to the basin divide limited the size of the subregions, which is an expected constraint in complex terrain. Scaling analysis was conducted by examining variance changes with spatial scale and tracking slope changes in the power spectra of simulated and observed backscattering fields through different snowpack phases (accumulation, ripening, and thawing). The power spectra of simulated and observed fields $|E(k)|^2$, where k is the wavenumber, can be modeled via a power-law like the form:

$$|E(k)|^2 \propto k^{\beta} \#(10)$$

in which the spectral slope β between two selected scales (or wavenumbers) can be estimated by applying the log transform to Eq. 10:

$$\beta \propto \frac{\log\left(|E(k)|^2\right)}{\log k} \#(11)$$

The spectral slope quantifies the backscatter energy distribution across scales, and changes in spectral slope between adjacent scales (i.e., scaling break) indicate a shift in scaling behavior. Following Manickam and Barros (2020), the working hypothesis is that snowpack physical property evolution leading to active microwave backscattering variation (Cao and Barros, 2020) can be identified by weather-driven changes in the scaling factor β. Identifying single-scaling behavior (β = constant) between two characteristic scales means that the backscatter fields at smaller scales can be upscaled to larger scales via fractal upscaling while preserving the spatial statistical structure (Bindlish and Barros, 1996).

4. Results and Analysis

4.1 DSMM Simulations

4.1.1 Snow Hydrology Regime

The predictive skill of the coupled MSHM-DCHM framework driven by HRRR 1st hour forecasts from the beginning of September 2016 to the end of June 2017 was assessed by comparison against streamflow observations at the SBB outlet, as well as time-series of observed SWE and snow depth at the two CSAS sites. **Fig. 9**a shows that the distributed model captures well the runoff peak time and the major melting periods after the onset of persistent melt in mid-May through the end of June. The discrepancy between cumulative HRRR and observed precipitation at SASP is ~0.2 m at the end of June, indicating an approximate 20% underestimation by HRRR. Interestingly, the difference was only 0.1 m on 3/1 and then doubled by 4/1 (**Fig. 9**b) because of a series of rain-on-snow events as illustrated by concurrent increased SWE and decreased snow depth (**Fig. 10**a and c) in the last two weeks of March, as well as temporarily lower albedo at SASP and SBSP (**Fig. 6**) in late March**.** The total HRRR snowfall underestimation inferred from the difference between the observed and simulated runoff is ~0.3 m (**Fig. 9**a). **Fig. 10**b and d suggest snowfall underestimation at high elevations (e.g., SBSP) is much smaller than that at lower elevations.

One implication of the HRRR precipitation underestimation and colder air temperatures (**Fig. 5**) is that the simulated volume backscattering in February and effective attenuation of snow-ground backscatter in April should be significantly lower than those detected by Sentinel-1. In addition, cold temperatures delay snowpack ripening, constrain daytime surficial melting, and hence reduce the number of refreeze-melt cycles (nighttime freeze followed by daytime melt) that impact snowpack microphysics, specifically the coarsening of the snowpack top layers.

4.1.2 Snow Microwave Behavior

The MEMLS-simulated total backscatter σ_{total} is the combination of volumetric backscatter , backscatter at the snow-air interface σ_{s-a}, and backscatter at the snow-ground interface σ_{s-g}. The temporal evolution of areal mean volume backscatter at X- (9.6 GHz) and Ku- (17.2 GHz) bands for each subregion and grid point (**Fig. 8**) across the SBB are illustrated in **Fig. 11** for HH and VH polarizations at 7 AM MST when surficial melting tied to insolation is minimized until the transition season. The phase-space maps reveal -SWE hysteresis loops similar to those over the Grand Mesa at 3 km resolution (Cao and Barros, 2020). The accumulation branch of the -SWE hysteresis loop presents a monotonic increase in backscatter with SWE throughout the cold season with stronger heterogeneity at grid-point scale and thus strong sensitivity that is the physical basis for immediate inference of SWE (i.e., SWE retrieval) from backscatter measurements when the snowpack is dry. There is negligible sensitivity in the ablation branch of the -SWE hysteresis loops at areal or point scales.

σ_{s-a} is tied to snow surface roughness patterns typically associated with wind redistribution of dry snow and surficial or deep snowmelt patterns. σ_{s-g} depends on roughness characteristics at the sub-grid scale as well as dielectric properties of the substrate. To quantitatively understand the time-evolving backscattering contribution at the air-snow and ground-snow interface as the snowpack stratigraphy and wetness change in response to weather, a suite of ensemble experiments was conducted for varying roughness patterns of snow and ground surface reflectivity (**Table 3**). In short, Ensemble 0 neglects σ_{s-a} and σ_{s-g}, Ensemble 1 neglects σ_{s-g}, and Ensembles 2-5 explore the sensitivity to reflectivity and the specular fraction of reflectivity (null for Ensemble 2 and 80% for Ensemble 5).

The temporal evolution of ensemble mean variability at C-band (5.6 GHz) in subregion A as a function of top-layer snow correlation length, top-layer liquid water content (LWC), and total SWE is examined in **Fig. 12** from February through June. Surficial melting caused by warming events results in large diurnal backscatter fluctuations, of which amplitude increases from February to June. Note the remarkable contribution of σ_{s-g} to total backscattering, as illustrated by the contrast between the backscatter range in Ensemble 1 (**Fig. 12**a) and Ensembles 2 (**Fig. 12**d) and 5 (**Fig. 12**g). For dry snowpacks in February, the uncertainty stemmed from ground surface reflectivity (Ensemble 5) is much more considerable than that at the snow-air interface (Ensemble 1) corresponding to an offset of about 10 dB. Further, the specular fraction of ground surface reflectivity controls backscattering sensitivity with an extensive range (uncertainty) when the snowpack is dry in February (**Figs. 12**d and g) that contracts as the snowpack ripens, LWC increases, and attenuation dominates (**Figs. 12**e and h, **Figs. 12**f and i). Strong daytime attenuation is associated with increased top-layer LWC, especially in June (**Fig. 12**f). Thus, the surficial melting pattern tied to topography is translated into spatial variability in the microwave domain. By the end of June, the amplitude of the diurnal cycle is controlled by LWC, and uncertainty within subregion A is determined by the diurnal cycle of shallow snowpacks with coarse grain size.

The temporal evolution of ensemble average backscatter variability in subregions A and C as a function of top-layer snow correlation length, top-layer liquid water content (LWC), and total SWE is examined in **Fig. 13**a (C-band) and b (X-band). The objective is to explore the frequency-dependent behavior at high (A) and low (B) elevations in late spring when snowpack melt is ongoing. The diurnal cycle of air temperature is characterized by warm daytime and cold nighttime values, with the durations above freezing being longer in C than in A. As the snowpack becomes progressively depleted and shallower, there is a rapid coarsening of the microphysics. This process, combined with melting that lasts longer in C than in A, results in negative diurnal fluctuations of backscatter. The contribution of σ_{s-g} is fully attenuated during daytime because of high LWC, and thus increment in total backscatter (Ensemble 1 v.s. Ensembles 2 and 5) only presents at night after the snowpack liquid water refreezes. **Fig. 13**b shows that the nighttime uncertainty is lower at X-band compared to C-band and higher in subregion C (low elevations, shallower snowpacks) compared to A (high elevations) in May, owing to the dominant contribution of ground backscatter to total backscatter. The sensitivity to daytime attenuation is higher at X-band, with no significant differences in the diurnal amplitude of backscatter fluctuations between A and C as the LWC in the top layer is the dominant control.

The Taylor diagrams in **Fig. S2**a synthesize -SWE sensitivity to model parameters (**Table 3**) quantified in terms of the standard deviation of the differences and the correlation coefficient between Ensemble 0 and each of Ensemble 1 (snowpack surface roughness), Ensemble 2 (ground surface reflectivity), and Ensemble 5 (Ensemble 2 with specified specular component) for the three subregions (A, B, and C) as a function of frequency (C-, X-, and Ku-bands) from December through June. For dry shallow snowpack conditions in December (~20 cm SWE, **Fig. S2**b), ground reflectivity is the dominant driver of sensitivity independently of frequency. Increasing specular reflectivity increases sensitivity at C-band for all snow-on conditions but only at X- and high Ku-bands for dry shallow snowpacks. The step-change in sensitivity between shallow and deep snowpack conditions at Ku-band is tied to the shallow penetration depth. The distinct behavior between C- and X- band for deeper snowpacks hints at the possibility of using changes in dual-frequency backscatter behavior to learn about snowpack vertical structure. Sensitivity to surface roughness is significant for shallow snowpacks; it can be neglected for deep snowpacks unless there are snow drifts and snow dunes as a consequence of wind redistribution and, or grid-scale mass transport processes that have not been considered here.

4.2 Scaling Behavior of Simulated Volumetric Backscatter

Following the aggregation scheme in Table 2 and using Ensemble 0 simulations at Sentinel-1 overpass time, the variance-area scaling relationship of simulated C-, X- and Ku-bands volume scattering -VV and -VH over the three subregions A, B, and C at 13:15 MST on three dates corresponding to accumulation (2017/2/19), ripening (4/25), and thawing (6/19) stages of the seasonal snowpack, are shown in **Fig. 14**. The variance is maximum at the native spatial resolution (i.e., the grid size of 30-m) and decreases with upscaling. The variance is higher in subregion C across all scales and decreases with elevation from C to A. Scaling breaks, regardless of subregion and frequency, occur between 120-180 m length scales, in agreement with results obtained by Manickam and Barros (2020) for Sentinel -1. This is confirmed by **Fig. S3** displaying similar Sentinel-1 area-variance curves for each subregion. Note the strong scaling break at 150 m over high-elevated subregion A for X- and Ku-bands capturing the emergence of snow on-off patterns in SBB (**Fig. S1)** in June**,** but not for C-band. This result suggests that X-and Ku-band measurements are more apt to contain information about snowpack spatial heterogeneity (i.e., snow cover gaps) than C-band.

The 2D spatial power spectra of simulated volume backscatter (**Fig. 15**) were examined to characterize scale-dependent backscattering structures tied to snow mass accumulation and snowpack stratigraphy during the snow season. The power spectra exhibited persistent single-scaling behavior in the 60-150 m scale range with a scaling break (denoted by the brown dashed vertical line at 150 m) and the flattening of spectra at longer wavelengths like the variance scaling break identified in **Fig. 15**. The flattening of the spectra is an artifact owing to the small domain size of SBB, thus constraining the range of scaling analysis. The spectral slopes in the 60-150 m wavelength range (delimited by green and brown vertical lines in **Fig. 15** top left panel) are summarized in Tables S3-S5 for -HH and -VH). Sentinel-1 spectra exhibit single-scaling behavior (**Fig. S4**) with slopes that closely match the ones from the simulations.

The minor differences in the shape of the power spectra in February (accumulation season, left panels in **Fig. 15**) for the same frequency imply that the distribution of snow mass on the terrain dominantly controls the volume scatter scaling behavior similar to that exhibited by Sentinel-1 observations over Grand Mesa (Manickam and Barros, 2020). The frequency-independent behavior persists through the end of April (mid-panels in **Fig. 15**), highlighting the robust physical basis of simulated backscattering structures for dry snowpacks, as well as the potential to exploit multi-frequency simulations to retrieve snow properties. By mid-June, the snowpack is shallower and patchy at high elevations reflecting solar insolation patterns and has vanished at low elevations, resulting in distinctive scaling behavior at 17.2 GHz (**Fig. 15** and **Fig. S1**). This suggests the potential utility of exploring these differences to infer snowpack conditions.

4.3 Radar Observing System Simulator (ROSS)

An intercomparison of simulated Sentinel-1 C-band SAR backscatter measurements and simulated total backscatter for daytime orbits over the SBB was conducted to evaluate DSMM's utility as a Radar Observing System Simulator (ROSS). Neglecting σ_{sr} as per the sensitivity analysis in Section 4.1.2, the total backscattering σ_{total} from the ground-snow-vegetation system at the grid scale can be decomposed as the following:

$$\sigma_{\text{total}}(t) = \sigma(t) + {}^{\sigma_{s-g}(t)+\sigma_{\text{veg}}(t)}_{\sigma_{\text{bkg}}(t)}\#(12)$$

where the snowpack volume backscattering and the backscatter at the snowpack-ground surface interface σ_{s-g} are simulated by the DSMM forward modeling system. Here, we refer to the sum of the backscattering contribution from the snow-ground interface σ_{s-g} and from the double-bounce scattering σ_{veg} representing snow-vegetation interactions that are not described in the DSMM as the background field σ_{bkg} in Eq. 12. Details on the ground dielectric properties, surface roughness, and landform at sub-grid scale (< 30 m) are unavailable, i.e., effective surface reflectivity is unavailable for SBB or generally elsewhere. Due to the complex topography and high spatial heterogeneity of land-cover and geological features in the SBB, calibration of model parameters at the grid-point scale is required, and forested areas would have to be masked off since vegetation scattering processes are not described in the model. Because the HRRR weather forecasts underestimate precipitation, calibration would result in anomalous estimates of surface reflectivity to compensate for the propagation of forecast errors in snow mass and snowpack conditions. Instead of calibration, we investigated the feasibility of utilizing Sentinel-1 backscatter information from snow-free conditions to estimate the upper bound $\sigma^{+}_{\mathrm{bkg}}$ which is the background contribution when the snowpack is dry and essentially transparent. As the snowpack changes include significant coarsening of microstructure, layering, and surficial melt, $\sigma_{\mathrm{bkg}}(t)$ contributed to the total backscatter can be described as a non-linear modification of $\sigma^{+}_{\mathrm{bkg}}$:

$$\sigma_{\mathrm{bkg}}(t) = \sigma^{+}_{\mathrm{bkg}} \times [1 - \gamma(t)] \, \#(13)$$

where the effective attenuation parameter $\gamma(t)$ quantifies the integrated impact of snowpack vertical structure.

Because the local incidence angle of an airborne or satellite-based instrument is modified by complex topography (**Fig. S5**), the viewing geometry was corrected pixel-by-pixel to account for the effect of the local slope steepness angle α:

$$\theta_c = |\theta - \alpha| \#(14)$$

where θ is the Sentinel-1 incidence angle and θ_c is the terrain-corrected viewing angle (Hoekman and Reiche, 2015; Vollrath et al., 2020). Sentinel-1 mid-day measurements in February over the SBB exhibit localized patterns of enhanced σ_{total}-VV and -VH backscatter (**Figs. 16**a and b) associated with high snowfall accumulation in mid-February at low elevations and moderate slopes (**Figs. 16**c and d), as well as attenuation owing to shallow snowpacks on steep slopes at high elevations when configuring the observational incidence angle within the 29.1° ~ 46° range (De Zan and Guarnieri, 2006).

Sentinel-1 backscatter measurements from eight daytime (descending) overpasses for snow-free conditions in the 2016 summer were first selected (**Fig. S6**) to estimate σ_{bkg} by averaging the backscatter fields in descending (daytime) orbits. σ_{bkg} ranges from -20 dB to 0 dB for VV polarization and captures well defined landform features showing much lower values over the west-facing steep slopes above the Senator Beck Mine, as well as the enhancement over the low-elevation forested areas and the rocky grasslands with mild slopes at mid-elevations (**Fig. S7** and **Fig. S8**). The utility of Sentinel-1 snow-free daytime measurements from individual overpasses in the summer and the fall several days after the last precipitation event (i.e., dry surface conditions) were also investigated to isolate the effects of soil moisture and surface temperature. A summary of mean Root Mean Square Deviation (RMSD) between the modified σ_{total} (sum of DSMM volume backscatter σ from Ensemble 0 and σ_{bkg} without attenuation correction) and Sentinel-1 backscatter measurements is presented in **Table 4** for different land-cover classes in SBB (see **Fig. S8** for land-cover map) on the same two dates in February (dry snowpack conditions) and April (ripening snowpack conditions) used in the scaling analysis.

Employing the summer daytime average backscatter to estimate σ_{bkg} yields the best RMSD with values below ±2.5 dB for dry snowpack conditions and below

±3.5 dB in the spring transition. The corresponding scatter plots in February and April are shown by **Fig. 17** and **Fig. 18**, respectively. The results are in good agreement with the Sentinel-1, especially for gentle and moderate slopes (30°) and bare ground and forested areas, albeit with lower bias and RMSD in February (**Table 5**). This is expected since dry snowpacks are almost transparent at C-band, and the backscatter at the snow-ground interface is dominant (Veyssiere et al., 2019) as opposed to the presence of surficial melting in April depending on topographic aspects.

The complex structure and heterogeneous distribution of intercepted snow in dense forests greatly reduce the SAR signal's sensitivity to the snowpack beneath the canopy (Montomoli et al., 2016). Indeed, there is a substantial underestimation of the highest backscatter values in Sentinel-1 (**Fig. 17**b) in February in the forest areas but not in April (**Fig. 18**b), which can be interpreted as the evidence of snow accumulation on the tree canopy tied to the interception that is not considered in DSMM and has melted by the end of April. This implies the potential challenges for independent SAR retrievals of SWE in forested areas if unconstrained by the time-series antecedent snow accumulation history to provide situational context regarding the snowpack below the canopy.

The statistics are generally poorer for the grasslands in the central SBB (**Table 4** and **Fig. 18**c), and more so in April during the spring transition when the ripening snowpack is also shallower. **Fig. S7** and **Fig. S8** illustrate that the grassland class from the 2016 National Land Cover Dataset should be reclassified into two distinct types: G1 - rocky outcrops with patches of alpine grass, and G2 - sparse forest and alpine grass on a complex escarpment. The high values of σ_{bkg} are therefore consistent with the ground surface roughness characteristics in G1. This points to the importance of accurate landcover classification at high spatial resolution (Löw et al., 2002) with critical implications for SAR remote-sensing. The DSMM predicts high LWC for grassland snowpack, which suggests that neglecting attenuation may be the principal cause for the overestimation of total backscatter on the moderate slopes of the central basin.

Since the separate contributions of volume and effective background scattering contributions are not known, the actual effective attenuation parameter $\gamma(t)$ inherent to the Sentinel-1 measurements is unavailable. To address this limitation, we hypothesize that the change in the difference between Ensemble 5 and Ensemble 0 backscatter from dry snowpack to ripe snowpack conditions can be used to estimate the effective spatially attenuation parameter that captures the evolution of simulated snowpack structure (**Fig. S9**a). Applying the attenuation correction in Eq. 13 results in significant improvements in mean bias on 2017/4/25 for moderate slopes up to 30°: a decrease from -1.1 to -0.2 dB for barren land and a decrease of -0.9 to -0.1 dB for grassland. Note that HRRR snowfall underestimation at mid-elevations where grassland dominates is slight (e.g., SBSP in **Fig. 10**). The improvement in RMSD is small because of high spatial variability in the aspect that affects the spatial distribution of surficial melt and the range of the attenuation parameter (**Fig. S9**b). The positive bias and RMSD increase for landcover classes in slopes > 30°, albeit for a small number of grid points with very steep slopes (e.g., **Fig. 18c**) at high elevations, suggesting the dry snowpack mass overestimation on steep slopes compounded with HRRR forecast errors in air temperature and wind. This overestimation could not be assessed in Section 4.1.1 due to the lack of ground observations. Nevertheless, substantial improvement suggests a straightforward path toward estimating surface reflectivity aided by physical modeling and observations in complex terrain. Therefore, ROSS experiments could be designed to backpropagate corrections from SAR measurements to improve the spatial snowfall distribution in the future.

5. Conclusions

The objective of this study to elucidate topographic controls on snow hydrology and active microwave behavior of seasonal alpine snowpacks. To this end, a coupled distributed snow hydrology-radiative transfer modeling framework DSMM (Distributed Snow Multiphysics Model), forced by interpolated weather forecasts (HRRR) at high spatio-temporal resolution (30-m, 15-min), was deployed to predict the spatial and temporal distribution of the snowpack structure and multifrequency radar backscatter across the Senator Beck Basin (SBB) in the Rocky Mountains, Colorado for the hydrologic year 2016-2017. The high resolution is necessary to capture the complex topography in the SBB and to match the spatial resolution of SAR measurements for forward modeling studies. Because of the resolution gap between the native resolution of the atmospheric forcing (3-km) and the DSMM resolution (30 m), elevation-pressure corrections were applied to improve the fidelity of the HRRR forecasts. DSMM fixed parameters are specified based on information about stable land-surface attributes from ancillary data and the literature, whereas time-varying parameters such as albedo are estimated from remote-sensing measurements wherever and whenever possible. Because existing standard albedo products at high elevations in the SBB were strongly affected by cloud contamination, a new high-resolution albedo product (30-m, 15-min) was derived from MODIS reflectance measurements using HRRR weather information to guide spatial interpolation. The SBB-specific albedo values compare well with albedo values derived from tower-based radiation fluxes, albeit overestimated late in the melt season. The latter could indicate spatial heterogeneity not being captured at the tower point-scale; however, the missed early spring melt runoff in the simulated streamflow suggests that the albedo is indeed overestimated at lower elevations, which has a positive feedback resulting in colder temperatures and delayed melt. Despite HRRR underestimation of precipitation at low elevations, DSMM prognostic simulations over the SBB capture well the observed runoff at the outlet, specifically the peak melt time.

Sensitivity analysis of parameters governing backscatter throughout the evolution of the seasonal snowpack agrees with the theory (e.g., Tsang and Kong, 2001; Tsang et al., 2000; Tsang et al., 1985). Ground surface reflectivity is the dominant driver of sensitivity and uncertainty at C- and X-bands in the accumulation season, and it decreases with frequency for deep snowpacks. For shallow snowpacks up to ~20 cm, sensitivity is independent of frequency. For the high Ku-band (17.2 GHz) sensitivity decreases qsharply after the dry snowpack exceeds 20 cm SWE. In the transition season, the temporal evolution of the ensemble variability shows the space-time distribution of surficial LWC and melt-refreeze cycles, which follows closely insolation patterns determined by topography.

The 2D power spectra of simulated backscattering fields exhibit consistent multiscaling behavior for dry snowpacks in the accumulation season: amplitude decreases uniformly with increasing frequency (and with decreasing penetration depth), and scaling breaks occur at ~150 m. During the ripening season starting in April, the spectra overlap consistent with frequency-independent behavior due to surficial melt effects dominating scattering. During the melt season (June), distinct power spectrum magnitudes at scales below the scaling break (< 150 m) are tied to the patchiness of snow-free gaps that also impacts the variance-area relationships at small scales. Overall, the scaling analysis of DSMM simulations is in agreement with results for Sentinel-1 in the SBB (this work) and in mountainous regions elsewhere (e.g., Manickam and Barros, 2020). The generality and physical-basis of these findings supports upscaling high-resolution SAR measurements in complex topography to spatial scales of 120-150 m, above which frequency-independent scaling behavior that depends only on SWE and snowpack physical properties prevails.

The Radar Observing System Simulator (ROSS) study further confirms there is a robust skill in state-of-the-art forward-modeling and interpretation of coupled snow hydrology and microwave backscattering at high resolution in complex terrain. Root Mean Square Deviations (RMSDs) between DSMM simualtions and Sentinel-1 do not exceed ± 3.2 dB for ripening snowpacks in early spring and ± 2.4 dB for dry snowpacks in the accumulation season. Grid-point RMSDs result from underestimated snowfall forecasts on upwind slopes and close-to-ground weather forecasting errors. Mean absolute bias is < 1 dB for all land-cover types on topographic slopes up to 30°, except for alpine grass on rocky outcrops (slopes 30°) due to underestimated attenuation of snow-ground interface backscatter. Application of a model-derived spatially and temporally varying attenuation correction of snow-ground scattering that captures place-based present-time snowpack conditions lead to decreases in bias at mid-elevations and moderate slopes by nearly one order of magnitude in the SBB. This suggests a pathway for physics-guided operational estimation of snowpack properties at high-spatial resolution enabled by SAR technology. Specifically, a modeling framework such as DSMM constrained by previous measurements via data-assimilation can be used to simulate snowpack structure and to separate ground scattering from volume scattering from SAR measurements either in the context of immediate or Bayesian inference, and thus improve the performance of SWE retrieval where ground-validation (GV) is not available for algorithm calibration.

Author Contributions

A.B. designed the research and analysis; Y.C. processed data, carried out model simulations, plotted graphs, and conducted quantitative analysis under the guidance of A.B.; Y.C. and A.B. wrote the manuscript cooperatively. All authors have read and agreed to the published version of the manuscript.

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Conflicts of Interest

The authors declare no conflict of interest.

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